TRAVEL TIME EXPENDITURE IN FLANDERS: TOWARDS A BETTER UNDERSTANDING OF TRAVEL BEHAVIOR

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Abstract: In modern societies, mobility is considered to be vital for human development. In order to lead an efficient policy and achieve environmental goals, governments require reliable predictions of travel behavior. In this paper, the travel time expenditure in Flanders is investigated. The focus is put on the time spent on commuting. Two modeling approaches are used for the analysis of daily travel time expenditure, namely the Poisson regression approach and the classical linear regression approach. In this paper it is shown that socio-demographics, day-effects and transportation preferences are contributing significantly in the explanation of variability in daily commuting time and that multiplicative effects of the transportation preferences form good approximations of the travel time ratios.

Keywords: travel time expenditure, daily commuting time, holiday effects, (Poisson) regression, travel time ratios

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1. INTRODUCTION

In modern societies, mobility is considered to be vital for human development: mobility is not only regarded as one of the driving forces behind economic growth, but also seen as a social need that offers people the opportunity for self-fulfillment and relaxation (Ministerie van Verkeer en Waterstaat, 2004). Reports from various international organizations, like for instance the European Commission's White paper "European transport policy for 2010: time to decide" (European Commission, 2004) indicate that governments acknowledge the essential role that mobility plays.

In order to lead an efficient policy and achieve environmental goals, such as the Kyoto norms, governments require reliable predictions of travel behavior. A better understanding of travel behavior will lead to better forecast and thus policy measures can be fine-tuned based on more accurate data.

In this paper, the travel time expenditure in Flanders (the Dutch speaking part of Belgium) is investigated. The focus is put on the time spent on commuting, where commuting trips are defined as school- and work-related trips. Travel behavior researchers have regained interest in the travel time budget (the daily travel time expenditure) in the context of activity-based and time use research in travel behavior modeling (Banerjee *et al.*, 2007). The notion of a constant travel time budget is thoroughly discussed in the literature (van Wee *et al.*, 2006).

2. OVERVIEW OF THE DATA

The data that will be used for the analysis stem from a household travel survey in Flanders that was carried out in 2000 (Zwerts and Nuyts, 2002). The focus of this survey was to investigate the travel behavior of the people living in the Flanders area. Since commuting was the primary motive for travel, as can be seen from Table 1, this paper focuses on investigating the daily time expenditure on commuting.

Table 1: Categorization of trips according to trip motive

Trips Motives	Nr. of Trips	% of Trips
Commuting	5633	26.80%
Shopping	4323	20.50%
Leisure	2992	14.20%
Non-commercial visits	2432	11.60%
Drop-off and Pick-up	2187	10.40%
Services (GP, Bank)	863	4.10%
Walking, Touring	732	3.50%
Business visits	506	2.40%
Other	1386	6.60%
Total number of trips	21054	100.00%

2.1 Daily commuting time

The daily commuting time is calculated by adding up the time spent on school- or work-related travel. Both the trips to the work/school locations and the trips back home were considered to be commuting trips. For this calculation all the respondents, that made at least one trip during the survey period (not necessarily a commuting trip), were considered. Figure 1 displays the distribution of the daily commuting times. Note that more than half of the respondents did not commute at all. The average time that the respondents spent on commuting was about 21 minutes.

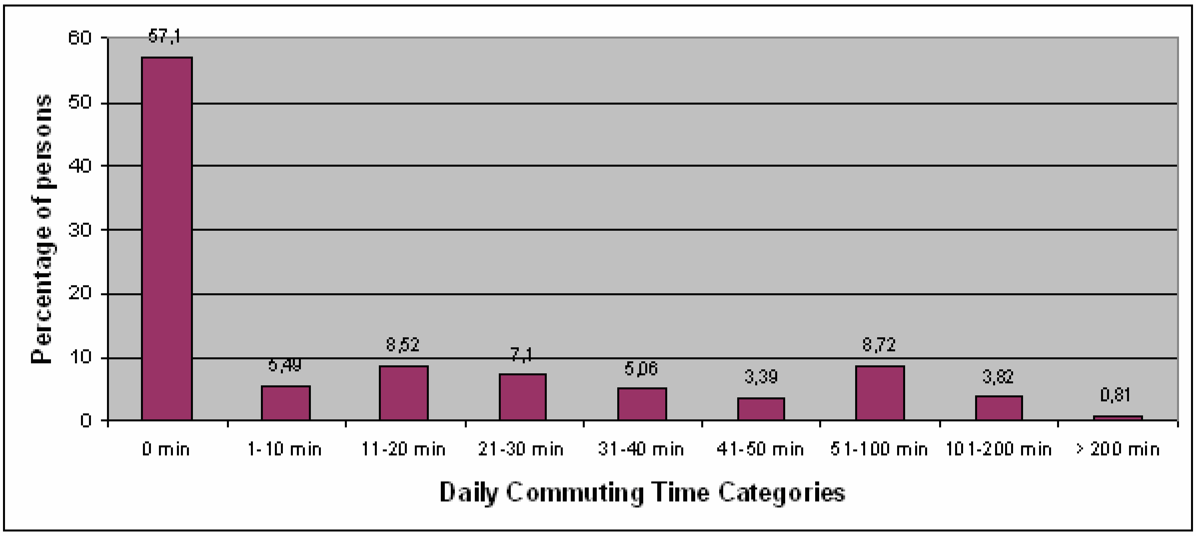

Figure 1: Distribution of Daily Commuting Time

2.2 Socio-demographics

Socio-demographic variables are commonly used in models that predict travel time (Frusti *et al.*, 2002, Sall, *et al.*, 2007). The following variables are used for the analysis presented in this paper: age, sex, and employment status. When Tables 2(a) and 2(b) are explored it can be seen that the daily commuting first increases with age, reaches his maximum at age category 35-44 and declines after people reach their retirement age. The daily commuting team seems to be a lot higher for males than for females and obviously the professionally active population spends more time on commuting compared to the inactive population.

Table 2(a): Descriptive statistics of *age*

	Daily Commuting Time (in minutes)		
Variable	Mean	St. Deviation	Nr of obs.
Age			
6-12	12.38	22.27	550
13-15	23.10	29.19	242
16-24	28.26	40.73	788
25-34	28.76	46.40	844
35-44	29.07	50.38	1169
45-54	25.43	52.39	1074
55-64	11.44	35.43	786
65+	1.41	12.59	608

Table 2(b): Descriptive statistics of *sex* and *employment status*

	Daily Commuting Time (in minutes)		
Variable	Mean	St. Deviation	Nr of obs.
Sex			
Male	26.05	50.58	3134
Female	16.53	31.90	2919
Employment status			
Housekeeping	0.68	5.89	401
Unemployed	2.57	10.57	179
Retired	1.33	15.16	881
Disabled	1.47	6.53	97
Pupil, Student	20.16	32.96	1348
Worker	31.04	48.93	912
Employee	33.29	53.71	1335
Executive	42.14	58.73	448
Liberal Profession	14.00	23.77	67
Self-Employed	24.43	46.13	261
Other, Non-Occupational	4.52	14.08	25
Other, Occupational	19.64	28.22	28

2.3 Day-effects

Next to the demographic variables, also some day-effects are used for the analysis.

Day-of-week effect

Agarwal (2004) showed that there exists a significant difference between travel behavior on a weekday and travel behavior on a weekend day. This difference is even further unraveled by Sall and Bhat (2007) demonstrating a significant day-of-week effect. For the analysis the day-of-week effect is represented in a categorical variable with seven categories; the first category corresponding to a Monday, the last to a Sunday.

Holiday effect

Liu and Sharma (2006) and Cools *et al.* (2007) indicated the importance of incorporating holiday effects into travel behavior models. To evaluate the significance of holidays on daily commuting time a special holiday variable is created, consisting of three categories: “normal days”, “holidays” and “summer holidays”. The following holidays are taken into account: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Sunday, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints’ Day and All Souls’ Day), and finally Remembrance Day. Note that for all these holidays, the adjacent weekends, were considered to be a holiday too. For holidays occurring on a Tuesday or on a Thursday, respectively the Monday and weekend before, and the Friday and weekend after, were also defined as a holiday, because often people have a day-off at those days, and thus have a leave of several days, which might be used to go on a long weekend or on a short holiday (Cools *et al.*, 2007) The days in July and August that were not in the above holiday list were labeled as “summer holidays”.

2.4 Transportation preferences

A final group of variables that is used for the analysis is the use of public transport services. The following transport services were considered: the use of the scheduled service bus, the use of the tramway service and use of the railroad system. As can be noted from Table 3, more than half of the respondents never use busses or trams. The use of trains is slightly more popular.

Table 3: Descriptive statistics for the use of public transport services

	Number of respondents using (percentage of respondents)					
Frequency	Bus		Tram		Train	
Daily	204	(3.59%)	85	(1.55%)	194	(3.46%)
A few times a week	289	(5.08%)	159	(2.90%)	158	(2.82%)
A few times a month	474	(8.34%)	280	(5.11%)	313	(5.58%)
A few times a year	1626	(28.60%)	1476	(26.96%)	2885	(51.44%)
Never	3093	(54.40%)	3475	(63.47%)	2058	(36.70%)

3. METHODOLOGY

Two modeling approaches are used for the analysis of daily travel time expenditure, namely the Poisson regression approach and the classical linear regression approach. The Poisson regression approach is defended by arguing that time expenditure can never take negative values. The classical linear regression approach can be justified by claiming that there is a widespread and continuous range of values that the travel time expenditure can adopt. This wide range is also witnessed from Figure 1. Comparing linear regression models with Poisson regression models is not a straightforward task. Therefore an objective criterion is constructed to compare the two types of models.

3.1 Exploratory data analysis: Regression tree

To get prior insight into the data, a regression tree is built through a process known as binary recursive partitioning. This is an iterative process of splitting the data into two partitions, and then splitting it up further on each of the branches. The algorithm chooses the split that partitions the data into two parts such that it minimizes the sum of the squared deviations from the mean in the separate parts. This splitting (or partitioning) is then applied to each of the new branches. The process continues until a saturated tree is grown. A tree is saturated in the sense that the nodes subject to further division cannot be split (Therneau and Atkinson, 1997). The terminal nodes are then recombined or “pruned” upwards to an optimal size tree. The degree of pruning is determined by cross-validation using a cost-complexity function that balances the apparent error rate with the tree-size. The optimal tree is the tree that corresponds to the complexity parameter that gives a minimum cost for the new data (Breiman *et al.*, 1984). Since no separate test sample was available, V-fold cross-validation was used as an alternative. A specified V value determines the number of random sub samples, as equal in size as possible, that is formed from the learning sample. The binary tree is then computed V times, each time leaving out one of the sub samples from the calculations. The sub sample that was not used in the calculations serves then as a test sample for cross-validation (CV). The CV costs computed for each of the V test samples are then averaged to give the V-fold estimate of the CV cost.

3.2 'Classical' linear regression

The classical linear regression approach is a modeling philosophy that tries to explain the dependent variable with the help of other covariates. Formally, the multiple linear regression model can be represented by the following equation:

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_{p-1} X_{i,p-1} + \varepsilon_i \quad (1)$$

where Y_i is the i-th observation of the dependent variable, $X_{i,1}$, $X_{i,2}$, …, $X_{i,p-1}$ the corresponding observations of the explanatory variables, β_0, β_1, β_2,…, β_{p-1} the parameters, which are fixed, but unknown, and where ε_i is the unknown random error. Estimates for the unknown parameters can be obtained by classical estimation techniques. If b_0, b_1, b_2, …, b_{p-1} are the estimates for the parameters, then the estimated value for the dependent variable Y_i is given by:

$$\hat{Y}_i = b_o + b_1 X_{i,1} + b_2 X_{i,2} + \ldots + b_{p-1} X_{i,p-1} \quad (2)$$

The following assumptions are made about the explanatory variables and the error terms.

- The error terms must be uncorrelated with the explanatory variables. If one of the explanatory variables is correlated with the error terms, it means that that covariate is correlated with unmeasured variables that are influencing the dependent variable.
- The assumption of homoskedasticity: the error terms must have the same variance for all values of the explanatory variables. Thus the predicted values of the independent variable must be equally good for all values of the explanatory variables.
- The values of the error terms have to be independent of one another. Non-independence leads to autocorrelation. This occurs when unmeasured variables are systematically similar between some pairs of observations.
- The error terms must be normal distributed. If the error terms are not normally distributed, the parameter estimate is usually also not normally distributed and thus the desirable characteristics of a normally distributed estimate would no longer be true.
- Absence of multicollinearity. The estimated parameter coefficients will be unstable and unreliable if explanatory variables are highly correlated. In the presence of multicollinearity, the effect of a single explanatory variable cannot be isolated, as the regression coefficients are quite uninformative and their confidence intervals very wide.

When these assumptions are satisfied, then the estimators for the parameters are BLUE (Best Linear Unbiased Estimators). Otherwise some remedial measures, like transformations, are required (Neter *et al.*, 1996).

3.3 Poisson regression

Explaining a dependent variable by means of other covariates is also the hands-on approach in Poisson regression. Instead of assuming independent normal distributed error terms like the classical linear regression approach, the Poisson regression technique is based on the assumption that the dependent variable is Poisson distributed. Formally, the model can be represented in the following way:

$$\log(E[Y_i]) = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_{p-1} X_{i,p-1} \quad (3)$$

or equivalently:

$$E[Y_i]) = exp(\beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_{p-1} X_{i,p-1}) \qquad (4)$$

where $E[Y_i]$ is the expected value of the i-th observation of the dependent variable, $X_{i,1}$, $X_{i,2}$, …, $X_{i,p-1}$ the corresponding observations of the explanatory variables, and β_0, β_1, β_2,…, β_{p-1} the parameters (Agresti, 2002). Estimates for the unknown parameters are obtained by maximizing the log likelihood using a ridge-stabilized Newton-Raphson algorithm (SAS Institute Inc., 2004).

The assumption of a Poisson distribution entails that the mean and variance of the presumed Poisson distributed variable must be (quasi-)equal. When the variance is significantly higher there is a problem of overdispersion. Potential overdispersion is taken into account by using the deviance as a dispersion parameter. Note that function obtained by dividing the log-likelihood function by the dispersion parameter is not a legitimate log-likelihood function, but a quasi-likelihood function. Nevertheless, most of the asymptotic theory for log-likelihoods also applies to quasi-likelihoods (McCullagh and Nelder, 1989).

3.4 Model comparison criterion

Comparing linear regression models with Poisson models is not a straightforward task. An objective criterion is needed to assess the performance of the two model approaches. Starting point is the determination coefficient (R^2) that is used in linear regression. This R^2 can be defined as the squared value of the Pearson correlation between the predicted values and the dependent variable. However, the Pearson correlation requires that the predicted values and the dependent variable are bivariate normally distributed. In classical linear regression this assumption is fulfilled when the residuals are normally distributed. However for Poisson models this assumption seems inappropriate. Therefore the Spearman correlations, which are non-parametric correlation estimates, form a more defendable basis for a comparison criterion. The new criterion, the Spearman Determination coefficient (Ψ^2), is defined as the square of the Spearman Correlation coefficient between the predicted and real values of the dependent variable. Formally the Spearman Determination coefficient can be represented in the following way:

$$\Psi^2 = \left(1 - \frac{6\sum_i d_i^2}{n\left(n^2-1\right)}\right)^2 \qquad (5)$$

where d_i is the difference between each rank of corresponding predicted and real values, and where n equals the number of observations (Cohen and Cohen, 1983).

4. RESULTS

4.1 Exploratory data analysis

The regression tree that is built through binary recursive partitioning is given in Figure 2. This tree is the pruned tree that takes into account a complexity parameter (cp) of 0.02548, minimizing the cost for new data. This cost was calculated by cross validation using 10 subsamples. Note that if fewer than 10 cross validations would have been used, the error rate of the tree could have been seriously overestimated (Breiman et al, *1984*).

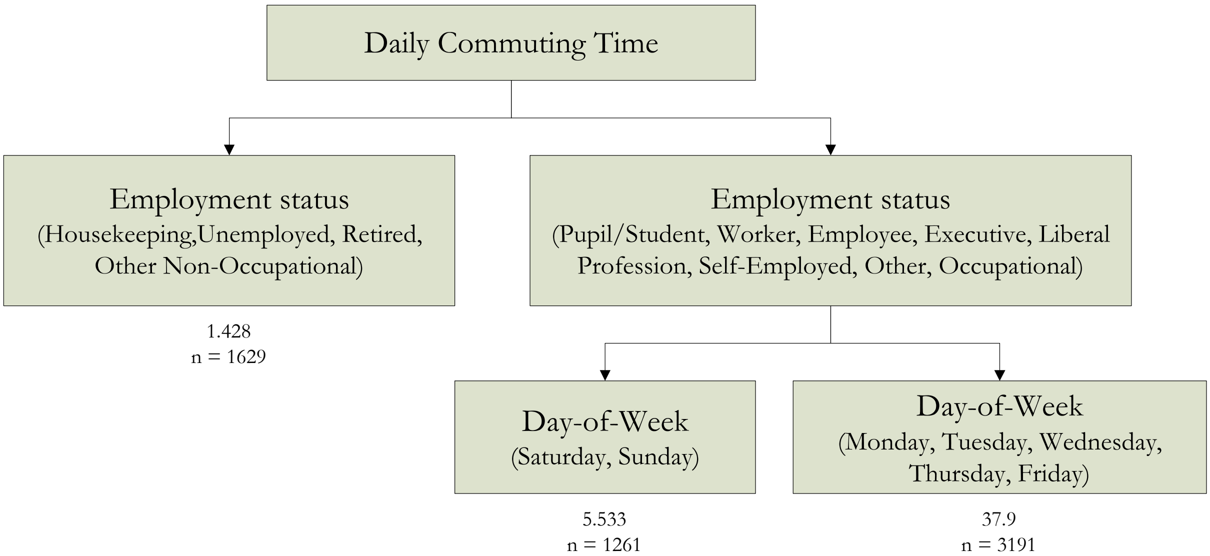

Figure 2: Binary regression tree for the daily commuting time

Figure 2 reveals that the employment status is the most important discriminator in explaining daily commuting time. As expected, the active population spends more time on commuting than their inactive counterpart. Next to the employment status, also day-of-week effects seem to be determining the daily communing time: during weekends people spent less time on going to work/school than during weekdays. Quite obviously this can be explained by the fact that most people only work during weekdays.

4.2 Linear regression

The variables that were used in the final linear regression model, together with their likelihood ratio (LR) statistics are displayed in Table 4. From this Table, it can be seen that all three categories of variables (socio-demographic variables, day effects and transportation preferences) are contributing significantly in the unraveling of daily travel time. The age effect, although insignificant, was kept in the model, because of the significant interaction effect between gender and age. Remind that p-values of interaction effects only have a valid interpretation when also the main effects are included in the model (Neter *et al*, 1996).

Table 4: LR Statistics (Type 3) For Linear Regression

Variable	DF	Chi-Square	P-value
Holiday	2	57.51	< 0.0001
Day-of-week	6	138.12	< 0.0001
Interaction Holiday/Day-of-week	12	32.19	0.0013
Age	7	5.45	0.6051
Sex	1	21.57	< 0.0001
Interaction Age/Sex	7	52.28	< 0.0001
Employment Status	11	239.50	< 0.0001
Scheduled service bus	4	53.12	< 0.0001
Tramway service	4	18.54	0.0010
Railroad system	4	118.79	< 0.0001

Table 5(a) shows the parameter estimates for the Linear Regression model. These Linear Regression parameter estimates can be interpreted as additive effects. If for instance the parameter estimates for Workers and Employees are compared, then the additive effect of being and employee instead of a worker can be calculated by a simple subtraction: 29.3025 – 25.9094 = 3.3931. This means that employees spent on average 3.3931 minutes more on daily commuting time than workers do, given that they share the same characteristics for the other variables.

By examining part a of the table, it can be seen that the active population obviously spends more time on commuting than the inactive population. The higher the position within a company, the more daily time is spent on commuting. Correspondingly, executives spend the most time on commuting. Also important to notice, is that people who use public transport (bus, train, tram) commute longer than the ones who seldom or never use public transport (20 up to 33 minutes longer).

Table 5(a): Parameter estimates for linear regression model

Parameter	Estimate	Parameter	Estimate
Intercept	-20.2705	**Use of scheduled service bus**	
Employment status		Daily	23.5018
Housekeeping	5.9466	A few times a week	3.3912
Unemployed	0	A few times a month	2.2725
Retired	0.5872	A few times a year	0.8242
Disabled	-0.9767	Never	0
Pupil, student	14.1228	**Use of tramway service**	
Worker	25.9094	Daily	19.5191
Employee	29.3025	A few times a week	-0.7410
Executive	34.3036	A few times a month	1.9913
Liberal Profession	11.3672	A few times a year	0.7206
Self-employed	18.5779	Never	0
Other, Non-Occupational	7.2682	**Use of train**	
Other, Occupational	18.3512	Daily	30.9260
		A few times a week	14.9523
		A few times a month	-3.3527
		A few times a year	-1.1999
		Never	0

Table 5(b): Total Effects for Day-of-week x Holiday Status

	Holiday Status		
Day-of-week	Normal day	Holiday	Summer Holiday
Monday	29.9273	19.2130	13.4156
Tuesday	32.1461	23.9021	13.6732
Wednesday	26.8283	19.6896	12.2422
Thursday	30.9206	9.4924	18.4244
Friday	25.0761	14.9622	16.4569
Saturday	1.7512	1.0133	-1.5522
Sunday	0	-2.5585	3.6116

Part b and c of the table give the parameter estimates of the total effects for respectively day-of-week and holiday status, and age and sex. Note that these total effects are calculated by adding up the parameter estimates for both main effects and the interaction effect. From Part b of the table it can be seen that during holidays, summer holidays and weekends people spent much less time on commuting than during normal weekdays. Part c of the table indicates that young females (06-24) commute longer than there peer males, while elder males (25+) commute longer than there females counterparts.

Table 5(c): Total Effects for Age x Sex

	Sex	
Age	Male	Female
6-12	-1.1889	1.5222
13-15	3.8782	7.5432
16-24	3.5454	4.8481
25-34	7.3532	-2.3521
35-44	13.5726	-5.087
45-54	11.8088	-3.4375
55-64	6.8192	-0.3207
65+	3.4970	0

4.3 Poisson regression

Table 6 displays the variables that were used in the Poisson regression model. To ease comparison between the two types of models, the same variables were taken into account as the linear regression model. From Table 6, one could observe that all three categories of variables (socio-demographic variables, day effects and transportation preferences) are playing a significantly role in the interpretation of daily travel time. Contrary to the linear regression model, the main age effect has a significant meaning in the Poisson regression model.

Table 6: LR Statistics (Type 3) For Poisson Regression

Variable	**DF**	**Chi-Square**	**P-value**
Holiday	2	54.85	< 0.0001
Day-of-week	6	492.48	< 0.0001
Interaction Holiday/Day-of-week	12	31.33	0.0018
Age	7	43.87	< 0.0001
Sex	1	34.17	< 0.0001
Interaction Age/Sex	7	90.00	< 0.0001
Employment Status	11	836.44	< 0.0001
Scheduled service bus	4	65.62	< 0.0001
Tramway service	4	20.20	0.0005
Railroad system	4	124.08	< 0.0001

The parameter estimates for the Poisson Regression model are shown in Table 7(a). These parameter estimates should be interpreted as multiplicative effects. Take as an example the parameter estimates for Workers and Employees. The multiplicative effect of being and employee instead of a worker can then be calculated in the following way: exp(2.3989 – 2.2852) = exp(0.1137) = 1.1204. This means that employees are commuting on average 1.1204 times longer (in terms of duration) than workers.

Table 7(a): Parameter Estimates For Poisson Regression Model

Parameter	Estimate	Parameter	Estimate
Intercept	-3.6835	**Use of scheduled service bus**	
Employment status		Daily	0.6008
Housekeeping	-1.1669	A few times a week	0.1356
Unemployed	0	A few times a month	0.0811
Retired	-0.2939	A few times a year	0.0346
Disabled	-0.5122	Never	0
Pupil, student	1.8745	**Use of tramway service**	
Worker	2.2852	Daily	0.4205
Employee	2.3989	A few times a week	0.0531
Executive	2.4739	A few times a month	0.0657
Liberal Profession	1.5340	A few times a year	0.0694
Self-employed	2.0230	Never	0
Other, Non-Occupational	0.7433	**Use of train**	
Other, Occupational	1.9887	Daily	0.5533
		A few times a week	0.4600
		A few times a month	-0.1808
		A few times a year	-0.0789
		Never	0

From part a of the table, it can be seen that the occupationally active people quite logically spend more time on commuting than occupationally inactive people. The higher the position people hold within a company, the more daily time they spend on commuting. Hence, similar results are obtained when compared to the classical regression model.

Another point that requests attention is the fact that people who use public transport (bus, train, tram) commute 1.52 (=exp(0.4205-0)) up to 1.88 (=exp(0.5533+0.0789)) times longer than the ones who seldom or never use public transport. Interesting is that these parameter estimates could be seen as approximations of the travel time factors, which are defined as ratios of the time spent for a certain trajectory using public transport to the time spent using a car. When these approximations are compared to the total travel time factor of 1.7 reported in the Flemish Mobility Plan (Ministerie van de Vlaamse Gemeenschap, 2001), one can conclude that the approximations work reasonable well and provide a more thorough look at the subject of travel time factor.

The parameter estimates of the total effects for respectively day-of-week and holiday status, and age and sex are given in Part b and c of the table. Remind that these total effects are calculated by adding up the parameter estimates for both main effects and the interaction effect. Part b of the table illustrates that during holidays, summer holidays and weekends people spent much less time on commuting than during normal weekdays. From Part c of the table on can notice that young females (06-24) commute longer than there peer males, while elder males (25+) commute longer than there females counterparts.

Table 7(b): Total Effects for Day-of-week x Holiday Status

	Holiday Status		
Day-of-week	Normal day	Holiday	Summer Holiday
Monday	2.2280	1.8591	1.5434
Tuesday	2.2954	2.0467	1.6203
Wednesday	2.1652	1.9151	1.5729
Thursday	2.2726	1.3858	1.8369
Friday	2.0943	1.6647	1.7334
Saturday	0.4598	0.2392	0.1621
Sunday	0	-0.3137	0.5161

Table 7(c): Total Effects for Age x Sex

	Sex	
Age	Male	Female
6-12	2.4047	2.5902
13-15	2.8718	3.0582
16-24	2.9321	2.9675
25-34	2.9882	2.6980
35-44	3.1630	2.4991
45-54	3.1886	2.5815
55-64	3.1480	2.6078
65+	2.7993	0

4.4 Model comparison

When the linear regression model is compared with the logistic regression model it is important to acknowledge that both model approaches yield consistent findings. One of the most important variables in explaining differences in daily commuting time is the employment status. Also Craviolini (2006) stressed the importance of this social status. Next to the employment status, the other socio-demographic variables that were taken into account, namely Age and Sex, were contributing significantly in explaining variability in daily commuting time. These findings are coherent with international literature on this subject (Bhat and Misra, 1999, Kapur and Bhat, 2007). Findings concerning the significant day-of-week effects and holiday effects were harmonious with the results reported in Lockwood *et al.* (2005) and Cools *et al.* (2007).

Table 8: Spearman Determination coefficient (Ψ^2)

Model Type	**Spearman Correlation**	**Ψ^2 (Psi-square)**
Poisson regression	0.66395	0.441
Linear regression	0.62344	0.389

Table 8 shows the Spearman Determination coefficient (Ψ^2) that can be used to assess the performance of the two model approaches. From this table one can see that this coefficient is higher for the Poisson regression and consequentially one can conclude that Poisson regression modeling is the approach to be preferred when trying to explain daily commuting time. The fact that the Linear regression model yielded both negative and positive values for the daily commuting time predictions, while the Poisson regression model only yielded positive values, favors the Poisson regression even more.

5. CONCLUSIONS AND FURTHER RESEARCH

In this paper it is shown that socio-demographics, day-effects and transportation preferences are contributing significantly in the explanation of variability in daily commuting time. Both the linear regression approach and the Poisson regression approach yielded findings that were consistent with international literature. When the performance of the two model approaches is evaluated, the Spearman Determination Coefficient favored the Poisson regression approach.

On of the most appealing results of this study is the fact that people who often use public transport (buses, trams or trains) spend more time on commuting than there counterparts who avoid using public transport services. An important question that could be raised is why these people still choose in favor of public transport: because of ease, comfort, safety? A stated-preference research might give an answer to this. Since commuting trips consume the largest part of the travel time expenditure, it is essential that policy makers acknowledge these findings. An essential step for stimulating the modal split, and thereby trying to achieve reliable travel times and environmental goals, such as the Kyoto norms, is the continuation of investments in public transport. Only when “acceptable” travel times are achieved by the public transport services, the general public will consider switching their transport mode. Choosing for those investments that reduce public transport travel times thus is a key challenge for policy makers.

In this paper it was evidenced that the multiplicative effects of the transportation preferences form good approximations of the travel time ratios. Thus, the reported Poisson methodology offers a framework that can be used to fine-tune policy measures.

Further investigation on other types of travel time expenditure (e.g. daily travel time expenditure on shopping or leisure) is necessary to realize a deeper understanding of Flemish travel behavior. Incorporation of other covariates, such as degree of urbanization, might even further illuminate the insights in travel behavior.

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